

Beyond residential segregation: A spatiotemporal approach to examining multi-contextual segregation

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1. Introduction

Segregation is an ongoing social problem in major U.S. cities. One may argue that there are some positive aspects of racial/ethnic segregation, such as maintaining ethnic communities and social ties or facilitating the migration process (Peach, 1996). From a geographic perspective, however, the segregation of the racial majority and minority groups of an area or region tend to have discriminatory consequences. For instance, when natural and social resources/infrastructure or polluting sources are not evenly distributed in space, the segregation between groups means that certain groups may be more clustered in environmentally less friendly and resource-poorer areas than the other groups. In general, racial minority groups have limited access to public services and fewer educational/employment opportunities and housing choices, and experience higher exposure to violence and environmental hazards (e.g., air pollution) which have negative impacts on their well-being and health.

Residential segregation has been well documented in the literature. In contrast, little is known about segregation that people experience in non-residential contexts. The traditional understanding of segregation within a residential context obscures a comprehensive examination of the complex and dynamic socio-spatial mechanisms shaping many social disparity issues. Further, several methodological problems inherent in residence- and place-based measures of segregation call for new fine-grained, people-based approaches (Hägerstrand, 1970). This study aims to make advances in conceptualizations and methods in segregation research. Moving beyond static concepts of residential segregation, it proposes a new dynamic notion of segregation that includes segregation in various geographic and temporal contexts in people's daily life, which is called *multi-contextual segregation*. It also suggests a new measure of multi-contextual segregation that can address the methodological problems in traditional measures. The usefulness of this new conceptualization and measure is illustrated by presenting a study of Atlanta, Georgia.

2. Literature review

For decades, many quantitative segregation studies have developed various indices (e.g., dissimilarity index (Duncan & Duncan, 1955)) to

measure how different racial groups are segregated based on their residential locations. However, those traditional indices of residential segregation have long been criticized as non-spatial measures (Ard, 2016; Morrill, 1991; Oka & Wong, 2015; Reardon & O'Sullivan, 2004; Wong, 1993, 2016) because they have two significant methodological problems (White, 1983): 1) a checkerboard problem (i.e., not accounting for spatial relationships between areal units within the entire area); and 2) the modifiable areal unit problem (MAUP) (i.e., a problem that occurs when artificially delineated areal units are used to analyze geographically continuous phenomena) (Openshaw, 1984).

Despite many efforts to “put some more geography” (Johnston, Poulsen, & Forrest, 2009) in segregation measures to address these two problems in many studies (e.g., Brown & Chung, 2006; Jones et al., 2014; Reardon & O'Sullivan, 2004; White, 1986; Wong, 2004), some researchers have been skeptical as to whether the spatial measures of residential segregation involve conceptually and theoretically sound notions of segregation (e.g., Reardon & O'Sullivan, 2004; Wong, 2016). Both the non-spatial and spatial measures of segregation focus only on the residential context. However, residential neighborhoods may not fully represent actual contexts in which individuals experience segregation given that people tend to spend a significant amount of waking time outside of their residential neighborhoods to conduct daily activities (Kwan, 2013). Segregation can occur in various daily life spaces, such as workplace and leisure activity places. Thus, restricting one's attention to residential contexts may lead to a great deal of uncertainty in research results. This issue has been referred to as *the uncertain geographic context problem* (UGCoP) (Kwan, 2012a), and this study argues that the UGCoP is the most important but least recognized methodological problem in both aspatial and spatial measures.

The UGCoP is a fundamental methodological problem that arises when spatially aggregated data are used with a coarse temporal resolution (Kwan, 2012a). It suggests that research results about the association between contextual (or environmental) factors and individuals' behaviors or health outcomes may be erroneous when the true geographic and temporal contexts experienced by people are misspecified (Kwan, 2012a,b; Park & Kwan, 2017a,b). For example, studies that have sought to link residential segregation to racial disparities in exposure to air pollution have yielded inconsistent research findings on the association (Ard, 2016),

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due in part to the UGCoP. Despite its importance, most quantitative studies on segregation have paid very little attention to the UGCoP and have continued to rely heavily on measures of residential segregation (Farber, O'Kelly, Miller, & Neutens, 2015).

Noting that people living in the same residential area may not experience identical levels of segregation (Wong, 2016), some recent studies have suggested that the scope of segregation-related research needs to be extended beyond the residential neighborhood to fully capture people's dynamic experiences of segregation in various contexts (e.g., Farber et al., 2015; Krivo et al., 2013; Kwan, 2013; Shelton, Poorthuis, & Zook, 2015; Wong & Shaw, 2011). Previous studies found that different racial/ethnic groups tend to work in different parts of an urban area by comparing residential and occupational segregation (e.g., Blumen & Zamir, 2001; Ellis, Wright, & Parks, 2004; Marciniak, Tammaru, Strömberg, & Lindgren, 2015; Toomet, Silm, Saluveer, Ahas, & Tammaru, 2015; Wright, Ellis, & Parks, 2010). However, such a binary approach can be a source of bias because it excludes non-working people, such as unemployed or retired people, and may underrepresent women by excluding full-time homemakers who are not employed in the labor market. Moreover, segregation is also observed at places for out-of-home non-work activities (e.g., social, recreational, and religious activities) (Dougherty, 2003; Sasidharan, And, & Godbey, 2005; Toomet et al., 2015).

Comprehensive examinations of the full spectrum of segregation are still at an early stage, and there is still no agreed term for it in the literature yet. It has been called variously as “time-space trajectories of segregation” (Atkinson & Flint, 2004) and “activity-space segregation” (e.g., Palmer, 2013; Wang & Li, 2015; Wang, Li, & Chai, 2012). However, neither of these terms embraces both time-geographic and activity-space approaches, as shown in some segregation studies that use activity-space approaches that do not take into account the time dimension, inevitably leading to some temporal uncertainties in their findings (e.g., Jones & Pebley, 2014; Schönfelder & Axhausen, 2003). Since every human activity occurs at a particular place for a certain period of time and thus space and time are inseparable, both space and time dimensions and their joint effect on people's daily mobility patterns should be considered as the principal variables for social studies (Hägerstrand, 1970). Suggesting the domains approach in segregation research, van Ham and Tammaru (2016) also emphasized the importance of including both time and space components in a conceptual framework of the domains approach. To facilitate a more explicit articulation of the research paradigm, there is a need for a more explicit and comprehensive term that describes the full picture of people's segregation experiences at various spatial and temporal contexts.

We propose a new notion of segregation, called *multi-contextual segregation*. Multi-contextual segregation is defined as the uneven spatiotemporal distribution of individuals of different social groups in various daily life contexts. The multiple contexts include not only various spatial contexts, such as workplace or leisure activity places, but also various temporal contexts in which an individual is situated. The spatial contexts are actually interlinked with the temporal contexts. Nighttime segregation is closely associated with residential segregation (Silm & Ahas, 2014), and daytime segregation likely occurs at workplace (Ellis et al., 2004). As a number of studies have reported that social and physical characteristics of people's daily activity locations have only weak associations with those of their residential areas (e.g., Jones & Pebley, 2014; Kestens, Lebel, Daniels, Thériault, & Pampalon, 2010; Shareck, Kestens, & Frohlich, 2014; Zenk et al., 2011), multi-contextual segregation is a theoretically more robust and meaningful concept than residential segregation.

Time geography introduced by Hägerstrand (1970) provides a useful framework for understanding multi-contextual segregation. People's patterns of daily mobility are influenced by various space-time constraints or mobility needs/preferences (Hägerstrand, 1970, 1989) as well as individual's socio-economic factors, transportation resources, and the spatial distribution of services and activities (Chaix et al., 2013). The differences in these factors among social groups often lead to different daily mobility patterns, which may shape multi-contextual segregation.

This new conceptualization of segregation calls for the development

of new fine-grained segregation measures, which in turn articulates a fundamentally new research paradigm. The advancements in geographic information science (GIS) and availability of fine-scale data that include individuals' spatiotemporal movement patterns (e.g., activity-travel survey data or mobile tracking data) have allowed researchers to examine segregation at high spatiotemporal granularity (Netto, Soares, & Paschoalino, 2015; Silm & Ahas, 2014; Toomet et al., 2015), or even at the individual level (Wong, 2016), which have contributed to mitigating the UGCoP (Kwan, 2012b). Examining segregation on an individual basis has been shown to be highly promising in some recent segregation studies (Farber, Pérez, & Morency, 2012; Netto et al., 2015; Schnell & Yoav, 2001; Wong, 2016; Wong & Shaw, 2011).

In light of the above discussion, this research argues that segregation studies need to move beyond simplistic understandings based on spatiotemporally fixed approaches, and that they should instead consider spatiotemporal population dynamics. This study seeks to address the following research questions: 1) Is there temporal variation in both segregation levels and its geographical patterns throughout the day in the study area? 2) Do racial minorities experience higher levels of segregation during the daytime (i.e., in non-residential areas) as well as at nighttime (i.e., in residential areas) than the majority group? 3) Do the measure of multi-contextual segregation and the measure of residential segregation produce significantly different values?

3. Data and methods

3.1. Study area

The study area is the greater Atlanta region (Georgia), one of the major metropolitan areas in the U.S. (Fig. 1). It is a metropolitan region with one of the largest concentrations of African American population in the U.S., sprawl-related long commutes, and a high level of automobile reliance (Bullard, 2000). Although Atlanta has been reported as one of the most diverse cities in the U.S., it also ranks as the second most segregated city (Silver, 2015). This is due to many problems that still linger in the area, such as racial discrimination in housing/mortgage and poor public transportation. These characteristics provide a useful context for investigating racial segregation. Further, the sprawl-induced spatial mismatch between work and home for low-income minorities would facilitate the identification of individuals' dynamic segregation experiences in various daily activity locations over the course of a day.

3.2. Data

This study uses an activity-travel diary dataset of 10,278 households

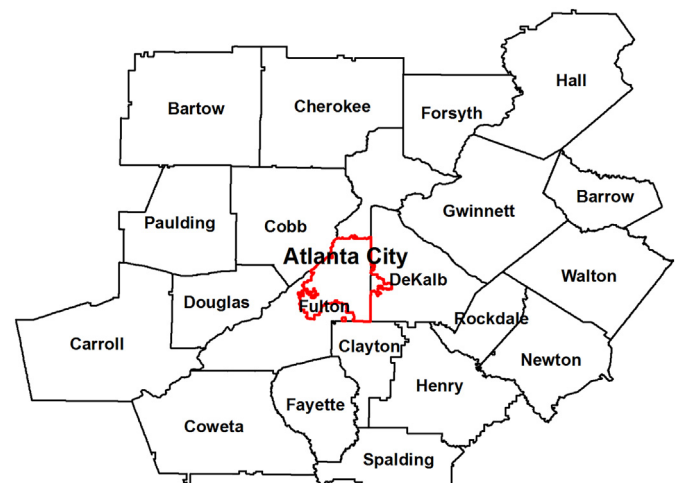


Fig. 1. Study area (the greater Atlanta region).

(25,810 persons) collected in the Atlanta Regional Commission (ARC) Regional Travel Survey (2011). It includes household and personal information and information about 93,713 trips (e.g., geocoded trip locations, activity types, travel times, and durations). Each survey participant reports all trips taken during a specified 24-hour period (a non-holiday weekday). For a more reliable projection from the sample to the entire population, the ARC used a stratified probability sampling method to ensure adequate, realistic representation of the population by area type across the region and by demographic group. The dataset is remotely accessible through the secure portal of the Transportation Secure Data Center (TSDC) in the National Renewable Energy Laboratory (2016) upon their approval. This dataset is the best option for this research in terms of its 1) detailed spatiotemporal information about individuals' daily trips that census data do not have; 2) richer information about personal characteristics than the vast amount of passive mobile positioning data or social media that do not usually include race information (Kwan, 2016); and 3) larger sample size compared to small-sample global positioning system (GPS) data, which allows us to obtain reliable results.

Information about race in the data is available at the household level, and the household race is classified as seven categories: white, African American, Hispanic/Mexican, Asian, Native American/Alaskan Native, Pacific Islander/Native Hawaiian, and multiracial household. Households that refused to report their race, that reported that none of the seven categories describes their race, or that said, "don't know," are removed from the samples. Multiracial households are also removed because the race of each household member cannot be identified. Then, the samples are reclassified into four racial/ethnicity groups: 1) non-Hispanic white (hereafter, white) (51.0%), 2) African American (31.1%), 3) Hispanic (10.9%), and 4) Others (i.e., Asian, Native American, Alaskan Native, Pacific Islander, and Native Hawaiian) (7.0%). Note that these proportions of the racial/ethnicity groups are the values after raking (sample-balancing), which well follows the population statistics in Census 2010. The raking technique is a method for adjusting the sampling weights of the sample data based on known population characteristics. It is also known as a sample-balancing, iterative proportional fitting, or raking ratio estimation technique. By adjusting the weights, the survey sample is forced to resemble the population, therefore making inference from sample to the entire population possible.

3.3. Methods

3.3.1. Phase 1. Measuring multi-contextual segregation

Phase 1 of this study examines multi-contextual segregation using a new method that integrates the modified version of Grannis's (2002) multi-group spatial proximity index and the k -nearest neighbors analysis. We call this method the *individual-level spatiotemporal proximity index* (i -STP index). Before using this index, a time frame and spatial range within which an individual's segregation index value is calculated are determined. Each individual's segregation level is then measured within the defined spatiotemporal context. All the analyses in Phase 1 are conducted using Python and R programming languages.

3.3.1.1. Determining the temporal unit. Since people's movement patterns tend to be relatively simple on weekdays compared to weekends due to some fixed daily activities (e.g., work), the use of an extremely fine temporal unit, such as every minute, would create many similar location points for each individual in the dataset, causing data redundancy. It may be inefficient for investigating the changes in the overall tendency of segregation over the course of a day. Therefore, in this study, a day is decomposed into seven time periods: the six 3-hour periods from 3 am to 9 pm and the 6-hour period from 9 pm to 3 am. Each individual thus has seven segregation index values during a day. The time from 9 pm to 3 am is considered one period because the segregation level is expected to be very similar during the period given that most people stay at home during that period. The 3-hour unit has

been used in other research that examined the temporal variation in segregation levels (Silm & Ahas, 2014).

3.3.1.2. Defining a person-specific neighborhood using the k -nearest neighbors analysis. Unlike Grannis's (2002) index that uses total population in an entire study area and thus generates a global value for the whole region, the i -STP index uses a population threshold k to define a person-specific neighborhood in which a segregation level is evaluated. k is a pre-defined count of the nearest neighbors from an individual's activity location in a given time period. The person-specific neighborhood defined by k -nearest neighbors reflects Tobler (1970)'s first law of geography—that an individual tends to be affected more by geographically nearer individuals than by those who are farther away. In addition, given that the individual may be influenced more by people who are temporally closer than those who are temporally farther away, a set of k -nearest neighbors may be different in different time periods. That is, in this study, k -nearest neighbors are close to the individual both in space and time. The k value can be defined differently depending on the characteristics of a study area (e.g., population density).

Fig. 2 shows a conceptual model for the i -STP index. Individual i 's person-specific neighborhood changes over time. Supposing $k = 3$, at t_1 , the three nearest neighbors are p_1 , p_2 , and p_3 , but at t_5 , they are p_4 , p_5 , and p_6 . This change in nearest neighbors and their spatial arrangement leads to temporal variation in segregation levels. If the black lines in Fig. 2 represent the daily movement paths of white people, and the gray lines represent those of African Americans, then at t_1 , i spends time in his/her person-specific neighborhood in which there are two white people and one African American, while at t_5 , there are one white person and two African Americans in his/her person-specific neighborhood. The i 's segregation level in a particular time period is determined by how these neighbors from different racial groups are spatially distributed within the i 's person-specific neighborhood during that time period.

Once the value of k is determined, k nearest neighbors of i are detected as follows: 1) Using the information on activity time durations in the activity-travel diary dataset, find all neighbors whose activity duration overlaps with i 's activity duration in a given time period (i.e., temporally close neighbors). 2) Among these neighbors, find k nearest neighbors based on the Euclidean distance between i and i 's neighbor (i.e., spatially and temporally close neighbors). Because the dataset does not include the information on the actual routes taken by an individual, and because locations a person passes by when moving are too fleeting to trigger segregation experience, the locations while traveling from one activity location to another are not considered in the analysis.

For example, in Fig. 3(A), the red line indicates i 's activity duration and the blue lines indicate neighbors' activity durations in the given

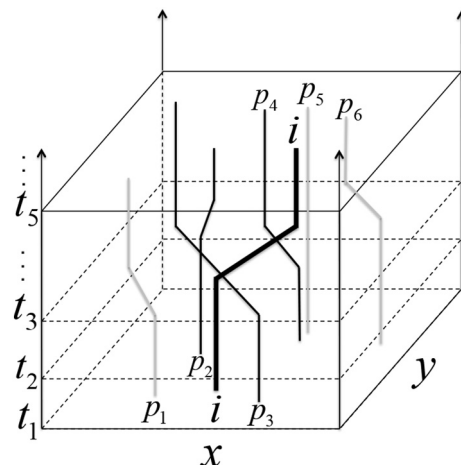


Fig. 2. A conceptual model of an individual's dynamic segregation experiences in different person-specific neighborhoods ($k = 3$) over time.

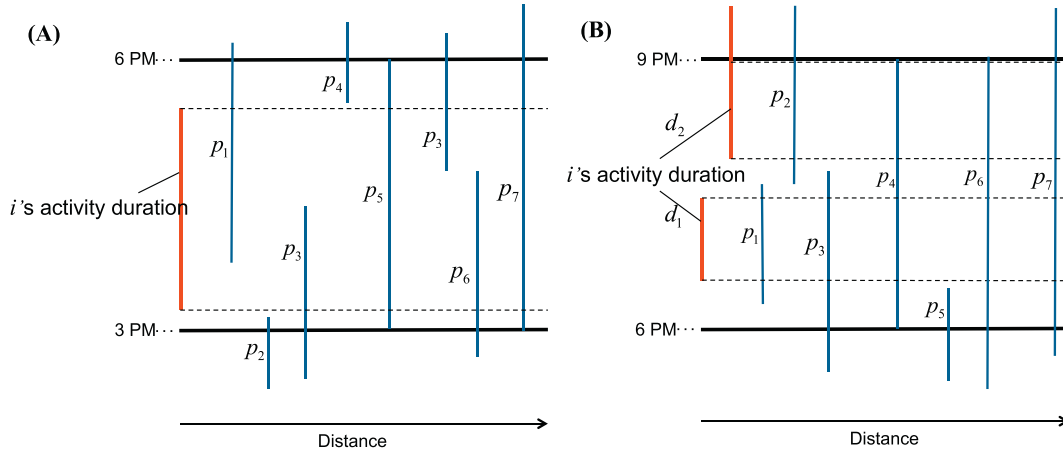


Fig. 3. Finding k nearest neighbors whose activity duration overlaps with i 's activity duration. (A): When i conducts one activity in a given time; (B): When i conducts more than one activity in a give time.

time period. Supposing $k = 3$, neighbors whose activity duration overlaps with that of i during that time period are $p_1, p_3, p_5, p_6,$ and p_7 . Among them, three nearest neighbors are $p_1, p_3,$ and p_5 . Note that p_3 conducts two activities at different locations during that time period. In this case, the activity location that is closer to i 's location is selected. Fig. 3(B) shows a case when i conducts two activities during one time period. During the first activity (d_1), three nearest neighbors are $p_1, p_3,$ and p_4 , while they are $p_2, p_4,$ and p_6 during the second activity (d_2). Using these different sets of nearest neighbors, segregation levels are measured separately first. Then these two values are averaged by weighting by its time duration to generate a single value of segregation index in this time period.

3.3.1.3. Calculating the segregation index at the individual level at different times of day. The i -STP index is inspired by Grannis's (2002) multi-group spatial proximity index. Grannis's index is a multi-group version of White's (1983) spatial proximity index that measures the relative proximity between the majority and minority populations using an inverse distance function. Putting the individual and time dimensions into Grannis's index and using the k -nearest neighbors analysis enable it to be modified as Eq. (1).

$$i - STP = \frac{\sum_{g=1}^n N_g P_{gg,t}}{k * P_{kk,t}} \quad (1)$$

where i -STP represents individual i 's spatial proximity index value during a specific time period t (e.g., $t = 1$ represents the time period 3 am–6 am). $P_{kk,t}$ is the average proximity between all k neighbors during t . $P_{gg,t}$ is the average proximity between individuals of g group among k neighbors during t . N_g is the number of individuals among k neighbors, which follows the proportion of g group in the city (the region-wide proportion of g group multiplied by k).

The use of the region-wide proportion of groups in k neighbors allows us to examine how evenly different groups of people are distributed in a person-specific neighborhood when assuming the same proportion of groups as region-wide are in the person's neighborhood. Reardon and O'Sullivan (2004) pointed out that a segregation measure for assessing spatial evenness should depend on the spatial distribution of people instead of the population composition. It is also noteworthy that the i -STP index uses individuals' exact daily activity locations, unlike most of Grannis/White's indices' applications that use centroids of each spatial unit (e.g., census tract) as residential locations.

The proximity between two points (p_i and p_j) can be defined in several ways. This study uses the proximity function based on a double

negative exponential function: $f(d_p p_j) = \exp(-2d_p p_j)$, where proximity decreases double-exponentially when the distance between the two individuals increases. Based on this function, $P_{kk,t}$ and $P_{gg,t}$ are defined as Eqs. 2 and 3.

$$P_{kk,t} = \frac{1}{k^2} \sum_i \sum_j f(d_{p_i p_j}) \quad (2)$$

$$P_{gg,t} = \frac{1}{N_g^2} \sum_i \sum_j f(d_{p_i p_j}) \quad (3)$$

The resulting index represents the average of intra-group proximities weighted by each group's fraction of k neighbors in a given time period. By repeating the computation for each time period, each individual has seven i -STP index values. Similar to White's (1983) interpretation, the i -STP index value of 1.0 indicates that an individual experiences no differential racial clustering in a given time period. A value > 1.0 means that an individual spends time in a neighborhood in which people are geographically closer to members of the same group as theirs than to those of other groups in a given time period. A value < 1.0 indicates that an individual spends time in a neighborhood in which people are geographically nearer to members of other groups than to those of the same group in a given time period.

3.3.1.4. Examining temporal variation in segregation levels and racial differences. The average segregation levels at different times of day are compared using a repeated measures ANOVA to assess whether they are significantly different. The repeated measures ANOVA is an extension of a standard ANOVA for non-independent groups. It is used when the same subjects are repeatedly measured over time under different conditions (i.e., segregation levels). To determine between which two time periods the differences occur and how much they differ, a post hoc test for ANOVA, called the Tukey's honest significant difference test, is carried out. Lastly, ANOVA and the Tukey's test are conducted to examine the racial differences in i -STP index values.

3.3.2. Phase 2. Geovisualizations of the temporal variation in segregation during a day

The geographic patterns of segregation at different times of day are visualized to identify the temporal variation in segregation patterns. Using GIS, individuals' i -STP index values in each time period that are assigned to activity location points are aggregated into a hexagonal grid surface. If individuals have more than one point in one period of time, those points are regarded as distinct points. Each hexagon is then color-coded based on the average segregation value of all individual points located in each

hexagon in a particular time period. Also, using ESRI's ArcScene 10.3.1, each hex bin is extruded vertically by its average segregation value to create a 3D hex bin. A number of different-sized hexagons are tested to best represent the data in manageable computational time. The resulting seven segregation maps are compared to each other in order to identify the temporal variation in segregation patterns during a day.

3.3.3. Phase 3. Comparing multi-contextual segregation with residential segregation

Phase 3 investigates whether multi-contextual segregation is different from residential segregation. First, residential segregation is measured at the individual level using k -nearest neighbors from individuals' residential locations. This measure, as most of the traditional measures of residential segregation do, assumes that people do not move from their home locations during the whole day. Thus, the temporal component is not considered in this measure. Next, the mean of the seven i -STP index values is calculated to generate the total daily level of multi-contextual segregation. This single value for each individual indicates the full daily segregation experienced during the whole day. Finally, the paired sample t -test is performed to see if there is a significant difference between the two measures.

4. Results

4.1. Results in phase 1

Because each individual should have one segregation index value for each 3-hour period, the respondents who did not report their activity information for longer than three hours are removed. People who traveled for longer than 3 h are also removed (e.g., flying to another state). As a result, 24,888 respondents remain and are used for the analysis.

Various k -scales are tested to find the population threshold that best captures the segregation tendency in the study area (see the sensitivity analysis in Appendix A). A population threshold of $k = 200$ is used in this study, considering the spatial distribution of the respondents across the study area. This means that each individual has two hundred neighbors for determining the segregation level of his/her person-specific neighborhood. To consider the difference in population density across the study area (e.g., the difference between the inner city and rural areas), we use a distance threshold (d) that limits the spatial range of a person-specific neighborhood. This makes individuals in areas with low population density have less than two hundred neighbors in their person-specific neighborhood, preventing them from having unrealistically large person-specific neighborhoods.

To set a distance threshold, we first calculate distances at which each individual finds the 200th neighbor from his/her location. As shown in the boxplot in Fig. 4, the minimum value of these distances is 1.401 km, while the maximum value (except the outliers) is 11.619 km. We choose the value of 75th percentiles (7 km; 6.713 is rounded up) as the distance threshold. 75% of the respondents find all two hundred neighbors within 7 km. For the rest of the respondents who do not have all two hundred neighbors within 7 km, only neighbors within 7 km are used to calculate the segregation index. If the number of neighbors of an individual within 7 km is < 30 , then the individual is discarded so that all individuals have at least 30 nearest neighbors. After applying these procedures, 23,178 individuals remain for the next step of the analysis.

After defining a person-specific neighborhood in each time period, segregation levels at different times of day are evaluated at the individual level using the i -STP index. Then the repeated measures ANOVA is performed to see if an individual experiences different levels of segregation at different times of day while conducting daily activities at various locations. The result shows that mean segregation level is significantly different at one or more time periods ($p < 0.001$). To see where these differences occur, the Tukey's test is used. As shown in Table 1, most of the differences between time periods are significant at a significance level of 0.1%. The smallest difference is found between t_3 (9 am–12 pm) and t_4 (12 pm–3 pm) although it is significant at a significance level of 1%. This

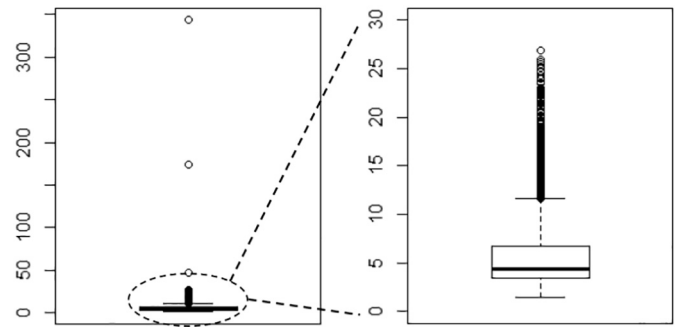


Fig. 4. Distribution of distances (km) at which individuals find their 200th neighbor.

may be because many people tend to be at work from 9 am to 3 pm and thus people may not move or may travel only a short distance between these two periods. This constrained mobility may lead to little change in their nearest neighbors and their spatial arrangement.

Fig. 5 displays varying segregation levels over the course of a day. The mean values of segregation levels (white marks on the boxplots in Fig. 5) decrease during the daytime and increase at night. This finding corresponds to the result of previous studies (Roux, Vallée, & Commenges, 2017; Silm & Ahas, 2014). Given that the data is collected during weekdays, the resulting daytime segregation is shaped most likely by individuals' work locations. It is also noteworthy that segregation levels during the daytime are less variable than the nighttime (Fig. 5), which suggests that regardless of race, people experience relatively similar levels of segregation during the daytime compared to the nighttime.

However, different racial groups may experience different levels of segregation during a day. The result of the ANOVA and Tukey's test indicates that all differences between racial groups are significant (Table 2). Based on the mean values of the segregation index, African Americans tend to experience higher levels of segregation than other racial groups, and whites experience the lowest levels of segregation overall (Fig. 6). Others including Asians are more integrated than the other minority groups, while Hispanics experience intermediate levels of segregation. This pattern is present for all of the time periods.

We conduct a sensitivity analysis with various sets of k and d values to determine whether changing any of these parameters lead to

Table 1
Pairwise comparisons between time periods (Tukey's test).

Difference of levels (time periods)	Difference of means	P-value
$t_2 - t_1$	-0.2800	< 0.001
$t_3 - t_1$	-0.5325	< 0.001
$t_4 - t_1$	-0.5246	< 0.001
$t_5 - t_1$	-0.3770	< 0.001
$t_6 - t_1$	-0.1819	< 0.001
$t_7 - t_1$	-0.0238	< 0.001
$t_3 - t_2$	-0.2525	< 0.001
$t_4 - t_2$	-0.2445	< 0.001
$t_5 - t_2$	-0.0970	< 0.001
$t_6 - t_2$	0.0981	< 0.001
$t_7 - t_2$	0.2562	< 0.001
$t_4 - t_3$	0.0079	0.0058
$t_5 - t_3$	0.1555	< 0.001
$t_6 - t_3$	0.3506	< 0.001
$t_7 - t_3$	0.5087	< 0.001
$t_5 - t_4$	0.1475	< 0.001
$t_6 - t_4$	0.3426	< 0.001
$t_7 - t_4$	0.5008	< 0.001
$t_6 - t_5$	0.1951	< 0.001
$t_7 - t_5$	0.3533	< 0.001
$t_7 - t_6$	0.1582	< 0.001

Note: t_1 : 3 am–6 am; t_2 : 6 am–9 am; t_3 : 9 am–12 pm; t_4 : 12 pm–3 pm; t_5 : 3 pm–6 pm; t_6 : 6 pm–9 pm; t_7 : 9 pm–3 am.

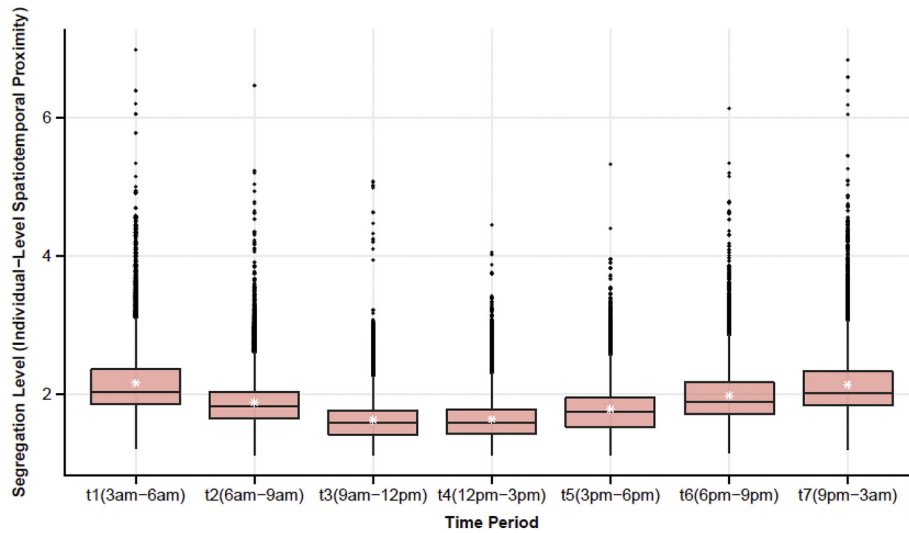


Fig. 5. Temporal variation in segregation levels during a day.

different conclusions of the findings. The sensitivity analysis results indicate that changes in the values of k and d do not significantly affect the primary analysis results, which strengthens the credibility of the findings (see Appendix A). Although the absolute numerical values of segregation may vary depending on the two parameters, they do not produce a significant change in the rank order of segregation values among individuals.

Interestingly, there are many more outliers with extreme values in the boxplot of whites when compared to those of other racial groups (Fig. 6). The most extreme outlier is found in the boxplot of whites. This demonstrates that some whites are most exclusively self-segregated from other racial groups. They are generally located in the exurbs of the greater Atlanta region. This geographic pattern is discussed in more detail in the next subsection.

4.2. Results in phase 2

The 3D geovisualizations in Fig. 7 show which part of the study area is highly segregated and in what time period segregation is greatest. With regard to the geographic pattern, high segregation is observed in the inner city and inner-ring suburbs for all time periods. African Americans are predominant in these areas both during the daytime and at night, indicating that many of them in the metropolitan region tend to work, live, and play in these areas. The increasing number of African Americans in the inner-ring suburbs—which were formerly predominantly white—is partially the result of rapid suburbanization of middle-class African Americans that has occurred since the 1970s (Pooley, 2015). The growing Asians and Hispanics also contribute to high segregation in the northern suburbs (Strait & Gong, 2015).

High segregation is also found in the exurbs (the low-density periphery of a metropolitan area), reflecting self-segregation of whites through the process of exurbanization (Pooley, 2015). As burgeoning non-white groups have moved to the suburbs, the white population has increasingly been

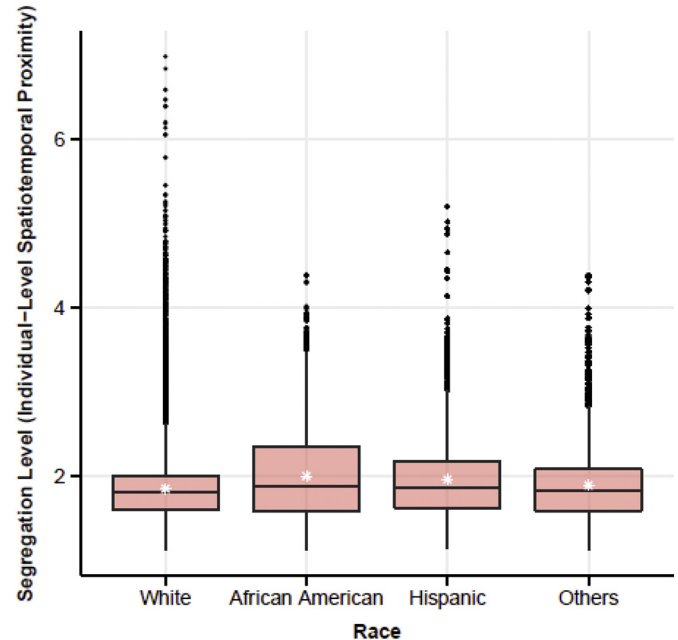


Fig. 6. Racial difference in segregation levels during a day.

moving from the inner-ring suburbs to the exurbs that are farther from the urban core (Pooley, 2015). It is notable that most tall hex bins with extremely high segregation levels are located in the exurbs. This is because there are at least a few individuals of all four racial groups in the inner city and inner-ring suburbs, whereas most people who live in the exurbs are whites, with only a few Hispanics, and African Americans or Others are rarely found. This indicates that whites, at least those who live in the exurbs, tend to have much stronger preferences for staying in their own race-dominant areas than other racial groups (Dawkins, 2004). The public transit network that ends right before the exurban counties accounts for the extreme segregation in the exurbs (Freemark, 2017).

The maps also show the temporal variation in segregation levels and its cyclical pattern. Overall, segregation levels are higher at night than during the daytime. From 3 am, segregation levels gradually decrease until noon, reach the lowest levels from 12 pm to 3 pm, and increase back after 3 pm. It implies that people may experience different levels of segregation when they are at home, work, and conducting out-of-home and non-employment activities over the course of the day. Interestingly, at t_4 —which is the time

Table 2

Pairwise comparisons between racial groups (Tukey's test).

Difference of levels (racial groups)	Difference of means	P-value
African American – White	0.1479	< 0.001
Hispanic – White	0.1049	< 0.001
Others – White	0.0377	< 0.001
Hispanic – African American	−0.0430	< 0.001
Others – African American	−0.1103	< 0.001
Others – Hispanic	−0.0673	< 0.001

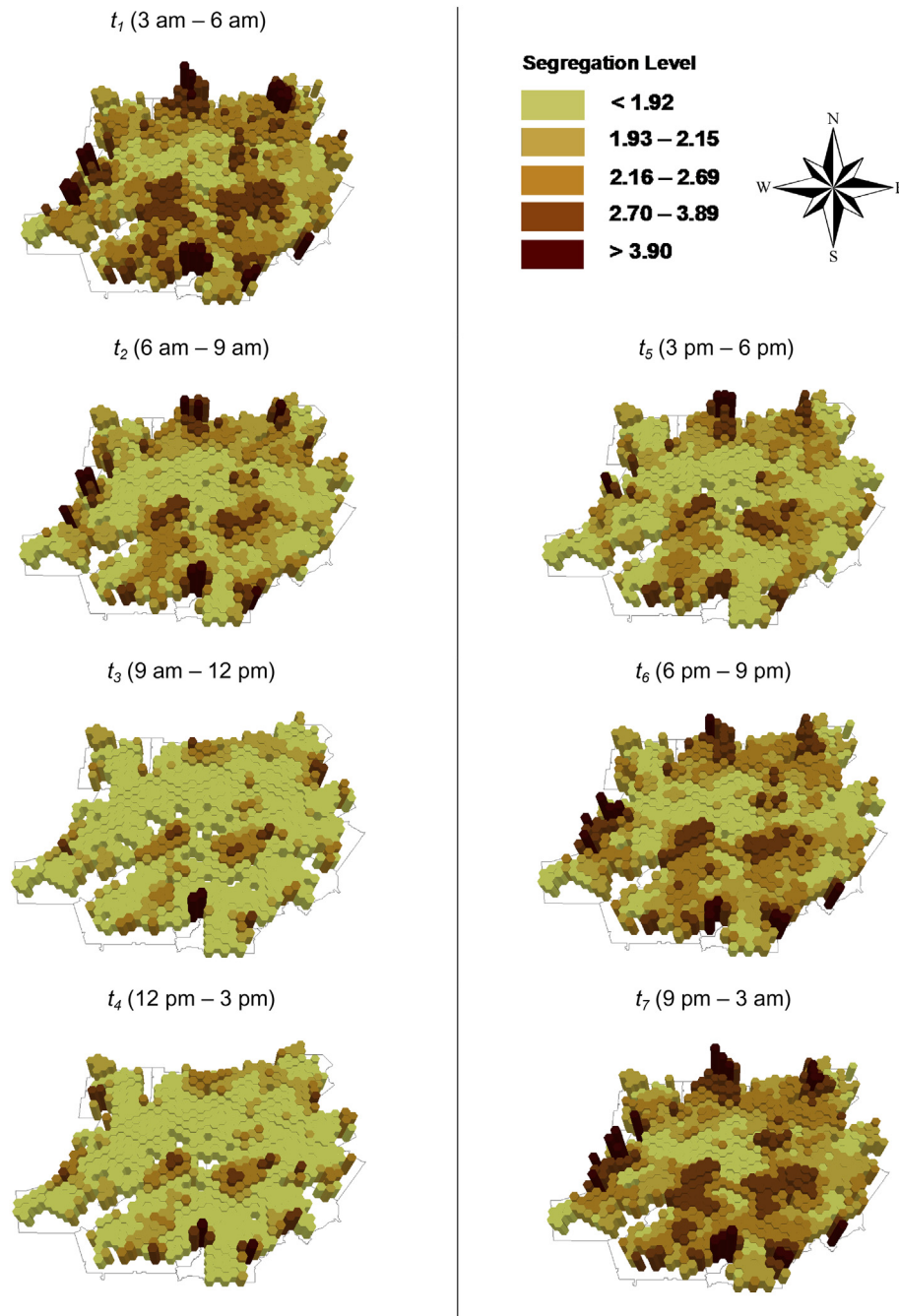


Fig. 7. Spatiotemporal patterns of segregation over the course of a day.

period when most of the people experience low levels of segregation (< 1.92), the segregation levels in the middle part of the metropolitan region including City of Atlanta remain high (> 2.70). This pattern indicates that the minority groups remain highly segregated and are more confined to the central city and inner suburbs at all time periods of a day. It means that home and job locations of the minority groups are geographically more constrained than those of whites.

The Metropolitan Atlanta Rapid Transit Authority (MARTA) system, a principal public transit service in the region, does not reach several dense employment centers in suburbs, which prevents racial minorities in the inner cities (who do not own private cars) from accessing those clusters (Freemark, 2017; Schmitt, 2014). It reflects the changing commuting pattern from 1990 to 2008 in the region that whites increasingly traveled in

both directions between the exurbs/outer suburbs (probably their home) and the inner city/inner-ring suburbs (probably their workplace), whereas such increase is not clear for African Americans and Hispanics (Jang & Yao, 2013). Racial discrimination in the transit system poses a major challenge to public transport planning that seeks to make transit lines reach the exurban counties, such as Cherokee and Fayette (Hatfield, 2013).

4.3. Results in phase 3

The total daily level of multi-contextual segregation for each individual is compared with the level of residential segregation. The result of the paired sample *t*-test indicates that the mean value of the total daily levels of multi-contextual segregation is significantly lower than

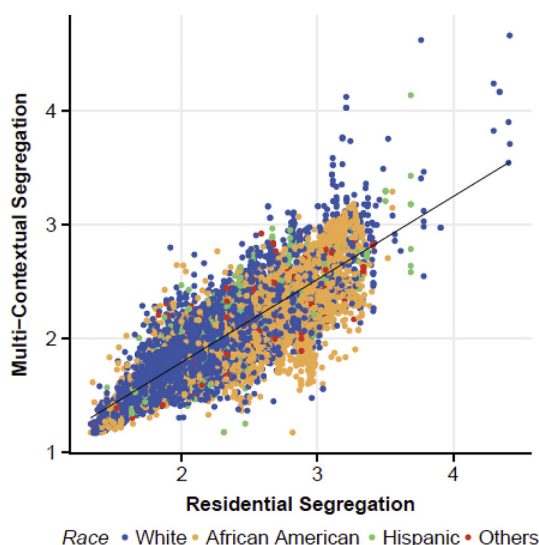


Fig. 8. Scatterplot of residential segregation versus multi-contextual segregation.

that of residential segregation levels (mean of the differences: -0.2433 ; $p < 0.001$). The relationship between residential and multi-contextual segregation is visualized in Fig. 8. The result indicates that people who live in highly segregated neighborhoods tend to work or conduct other daily activities in relatively more integrated urban areas than their residential neighborhoods.

Fig. 9 shows an example of this. The three respondents (Persons 1, 2, and 3) in this graph live in City of Atlanta and are members of the same African American household. City of Atlanta is a highly segregated area both during the daytime and at night as shown in Fig. 7. Fig. 9 shows that these three persons experienced very different levels of segregation throughout the day depending on where they spent their waking time. The segregation levels of Persons 1 and 2 change significantly over time whereas Person 3 experiences very similar levels of segregation for all the time periods. In greater detail, Person 3 stayed at home and went grocery shopping in her residential neighborhood in City of Atlanta, while Person 1 left home early in the morning and worked in the outer suburb during the daytime. At t_3 , Person 1's i -STP index value is 1.28. Given that an index value equal to 1.00 indicates no differential racial clustering, Person 1 experienced almost integration of population in his workplace during that time period.

5. Discussion and conclusions

This study examines segregation that individuals experience in various space-time contexts in their daily life using an activity-travel diary dataset

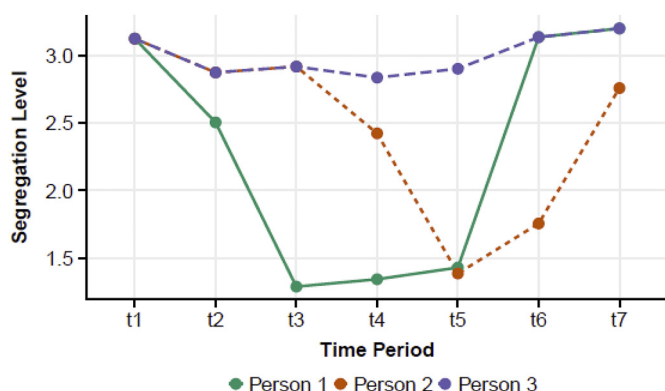


Fig. 9. Within-household variation in segregation levels.

and an individual-level spatiotemporal proximity index as a measure of multi-contextual segregation. The major finding is that people in the greater Atlanta region experience varying levels of segregation over the course of a day depending on where they spend their time.

This study has several limitations. First, although the proposed segregation index takes various daily life contexts into account, it does not capture segregation that may occur at the micro scale—within a building or a workplace. For example, in places for activities based on common interests, such as watching sport games, people from different racial groups may seemingly be integrated because they are at the same stadium. However, when looking more closely, people of different race, ethnicity and income levels may seat in different areas, reflecting segregation in the micro spatial environment of the stadium. Another example is the geographic separation of employees within a workplace. Minority workers tend to be located in the back offices or kitchens, whereas the front offices tend to be occupied by people from a dominant group (Vallas, 2003). Although such “micro inequities” might seem insignificant, they have a powerful effect on the reproduction of racial/ethnic boundaries within workplaces (Creese, 2011). This micro-scale segregation is another important aspect of segregation that needs to be examined in future research. Such research will provide more fruitful insights into the micro-geographic dynamics of segregation, marginalization, and social disparities that are mutually constitutive with segregation (Kwan, 2013).

Second, segregation that people may experience when commuting or traveling is not examined in this study because there is no information on the respondents' actual travel routes. Note that minorities tend to rely more on public transit than whites, and often most passengers in a bus or train are minority people. Such segregation resulting from the use of different travel modes may be better examined using GPS tracking data and qualitative methods. Lastly, the results of this study may be affected by how the time frame is defined because it uses a 3-h period as the temporal unit of analysis for examining the temporal variation in segregation levels. This issue has recently been articulated as the modifiable temporal unit problem (MTUP) (Cheng & Adepeju, 2014). Further experiments of temporal discretization will be needed to see if the overall spatiotemporal patterns of segregation in this study can be consistently observed no matter what temporal unit is used.

Despite these limitations, this study contributes to advancing in the conceptualizations and methods in segregation research. A single value of traditional global measures of segregation may inform us whether the whole city or metropolitan region is segregated or not, but it cannot tell us where, when, and how much segregation people experience dynamically throughout a day. Moving from place-based to people-based approaches can provide a better understanding of dynamic human space-time behaviors (Kwan, 2009). The dynamic notion of segregation and the individual-level measure proposed in this study provide insights into how people are spatiotemporally distributed throughout the day. This people-based measure is especially useful because it can be directly linked to other individual-level variables to examine critical issues related to dynamic human space-time behaviors, such as personal levels of exposure to air pollution, personal dietary intake, and health/medical history. If the measure is used to examine the effect of segregation on health disparities associated with exposure to air pollution or dietary intake, it would yield new insights into how those health disparities are shaped through the uneven spatiotemporal distribution of different social groups in various everyday life contexts.

The spatiotemporal approach in this study also helps mitigate methodological problems such as the UGCoP, MAUP, and checkerboard problem. The UGCoP is an important concern since it can lead to inferential errors or misleading findings (Kwan, 2012a; Park & Kwan, 2017a, 2017b). Recent studies have paid increasing attention to the problem. For example, Zhang and Thill (2017) developed a network analysis approach that detects the space-time contexts of distinct communities (i.e., where within-community interaction is greater than between-community interaction) by examining the relational ties between individuals and the space-time interconnectedness of people's

activity trajectories. This approach is promising for addressing the UGCoP as well as the MAUP.

Further, this study helps facilitate desired societal changes in a broad context. Although this research focuses on Georgia, the proposed concept and method are widely applicable to other study areas. It also generates more nuanced knowledge for future policy recommendations. Along with the existing policies for residential mixes among racial groups, policymakers and urban planners should also try to improve the daily mobility of marginalized social groups or racial minorities to diverse parts of urban areas by planning a more just regional transit system. Lastly, the geovisualization results would help promote the general public's awareness and understanding of the unfair use of urban space in their everyday life. This newfound understanding would bolster minorities' resolve to participate more actively in policy decision processes or relevant surveys. All of these efforts would facilitate the engagement of the general public, academics, and policymakers in

constructive conversations about a wider range of social disparity issues stemming from racial segregation.

Declaration of interest

The authors declare no conflict of interest.

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Appendix A. Sensitivity analysis

We tested various sets of k (the number of nearest neighbors) and d (a threshold distance) values (Table A.1) to assess whether changing any of these parameters may lead to different conclusions.

Table A.1
Different pairs of k and d parameters for sensitivity analysis.

k	100	100	200	200	200	200	200	400	400	400
d (km)	5	7	5	7	10	12	17	10	12	17

Note: Bolded values indicate selected values for k and d parameters.

The sensitivity analysis result shows that the smaller the k and d values are, the higher the segregation levels are in general. Likewise, if the two values are higher, the segregation levels tend to decrease. This result is reasonable because it is likely that people are more homogeneous if their person-specific neighborhood (delineated by k nearest neighbors) is smaller. However, the sensitivity analysis result indicates that the change in k and d values does not significantly affect the segregation analysis results. Although the absolute numerical values of segregation may vary depending on the two parameters, they do not produce a significant change in the rank order of the segregation values for the respondents. Even with different k and d values, the temporal variation and racial differences in segregation levels have almost the same patterns, and most of the differences remain statistically significant (exceptions: when d is 5, the difference between t_3 (9 am–12 pm) and t_4 (12 pm–3 pm) is not significant (Table A.2); when k is 100 and d is 7, the difference between African Americans and Hispanics is not significant (Table A.3)). When considering the spatial distribution of the samples across the study area, the k value of 100 makes the size of a person-specific neighborhood too small (especially in cities) and the k value of 400 makes it too big to capture local variations in segregation in the study area.

Table A.2
Temporal differences in segregation levels (different pairs of k and d parameters).

	$t_2 - t_1$	$t_3 - t_1$	$t_4 - t_1$	$t_5 - t_1$	$t_6 - t_1$	$t_7 - t_1$	$t_3 - t_2$	$t_4 - t_2$	$t_5 - t_2$	$t_6 - t_2$
$k = 100; d = 5$	-0.2790***	-0.5364***	-0.5298***	-0.3795***	-0.1798***	-0.0193***	-0.2574***	-0.2508***	-0.1005***	0.0992***
$k = 200; d = 5$	-0.2804***	-0.5283***	-0.5213***	-0.3774***	-0.1809***	-0.0213***	-0.2479***	-0.2409***	-0.0967***	0.0995***
$k = 100; d = 7$	-0.2791***	-0.5399***	-0.5317***	-0.3796***	-0.1807***	-0.0221***	-0.2609***	-0.2526***	-0.1005***	0.0983***
$k = 200; d = 7$	-0.2800***	-0.5325***	-0.5246***	-0.3770***	-0.1819***	-0.0238***	-0.2525***	-0.2445***	-0.0970***	0.0981***
$k = 200; d = 10$	-0.2788***	-0.5325***	-0.5239***	-0.3756***	-0.1833***	-0.0249***	-0.2537***	-0.2450***	-0.0968***	0.0956***
$k = 400; d = 10$	-0.2761***	-0.5232***	-0.5154***	-0.3701***	-0.1745***	-0.0239***	-0.2470***	-0.2392***	-0.0940***	0.1017***
$k = 200; d = 12$	-0.2787***	-0.5328***	-0.5250***	-0.3750***	-0.1831***	-0.0251***	-0.2541***	-0.2463***	-0.0964***	0.0955***
$k = 400; d = 12$	-0.2765***	-0.5253***	-0.5186***	-0.3709***	-0.1744***	-0.0241***	-0.2488***	-0.2421***	-0.0944***	0.1021***
$k = 200; d = 17$	-0.2786***	-0.5311***	-0.5241***	-0.3735***	-0.1826***	-0.0249***	-0.2525***	-0.2454***	-0.0949***	0.0960***
$k = 400; d = 17$	-0.2796***	-0.5282***	-0.5222***	-0.3720***	-0.1756***	-0.0230***	-0.2486***	-0.2426***	-0.0924***	0.1040***

	$t_7 - t_2$	$t_4 - t_3$	$t_5 - t_3$	$t_6 - t_3$	$t_7 - t_3$	$t_5 - t_4$	$t_6 - t_4$	$t_7 - t_4$	$t_6 - t_5$	$t_7 - t_5$	$t_7 - t_6$
$k = 100; d = 5$	0.2597***	0.0065	0.1569***	0.3566***	0.5170***	0.1504***	0.3501***	0.5105***	0.1997***	0.3601***	0.1604***
$k = 200; d = 5$	0.2590***	0.0070	0.1509***	0.3474***	0.5069***	0.1439***	0.3404***	0.4999***	0.1965***	0.3560***	0.1595***
$k = 100; d = 7$	0.2570***	0.0082*	0.1604***	0.3592***	0.5178***	0.1521***	0.3509***	0.5096***	0.1988***	0.3575***	0.1587***
$k = 200; d = 7$	0.2562***	0.0079**	0.1555***	0.3506***	0.5087***	0.1475***	0.3426***	0.5008***	0.1951***	0.3533***	0.1582***
$k = 200; d = 10$	0.2539***	0.0086***	0.1569***	0.3492***	0.5076***	0.1482***	0.3406***	0.4989***	0.1924***	0.3507***	0.1583***
$k = 400; d = 10$	0.2522***	0.0078***	0.1531***	0.3487***	0.4993***	0.1452***	0.3409***	0.4915***	0.1957***	0.3462***	0.1506***
$k = 200; d = 12$	0.2536***	0.0078**	0.1577***	0.3496***	0.5077***	0.1500***	0.3419***	0.4999***	0.1919***	0.3499***	0.1580***

(continued on next page)

Table A.2 (continued)

	$t_7 - t_2$	$t_4 - t_3$	$t_5 - t_3$	$t_6 - t_3$	$t_7 - t_3$	$t_5 - t_4$	$t_6 - t_4$	$t_7 - t_4$	$t_6 - t_5$	$t_7 - t_5$	$t_7 - t_6$
$k = 400; d = 12$	0.2524***	0.0067***	0.1544***	0.3509***	0.5012***	0.1477***	0.3442***	0.4945***	0.1965***	0.3468***	0.1503***
$k = 200; d = 17$	0.2537***	0.0070*	0.1575***	0.3485***	0.5062***	0.1505***	0.3415***	0.4992***	0.1909***	0.3486***	0.1577***
$k = 400; d = 17$	0.2566***	0.0060**	0.1562***	0.3526***	0.5052***	0.1502***	0.3466***	0.4992***	0.1964***	0.3490***	0.1526***

‘p > 0.05.

*** p ≤ 0.001.

** p ≤ 0.01.

* p ≤ 0.05.

Table A.3

Racial differences in segregation levels (different pairs of k and d parameters).

	AA-W	H-W	O-W	H-AA	O-AA	O-H
$k = 100; d = 5$	0.1892***	0.1715***	0.0874***	−0.0176*	−0.1017***	−0.0841***
$k = 200; d = 5$	0.1569***	0.1266***	0.0492***	−0.0303***	−0.1077***	−0.0774***
$k = 100; d = 7$	0.1787***	0.1642***	0.0808***	−0.0144	−0.0979***	−0.0835***
$k = 200; d = 7$	0.1479***	0.1049***	0.0377***	−0.0430***	−0.1103***	−0.0673***
$k = 200; d = 10$	0.1469***	0.0956***	0.0364***	−0.0512***	−0.1105***	−0.0592***
$k = 400; d = 10$	0.1043***	0.0586***	0.0175*	−0.0457***	−0.0868***	−0.0412***
$k = 200; d = 12$	0.1474***	0.0908***	0.0362***	−0.0566***	−0.1112***	−0.0546***
$k = 400; d = 12$	0.1046***	0.0490***	0.0191**	−0.0556***	−0.0855***	−0.0299***
$k = 200; d = 17$	0.1479***	0.0915***	0.0378***	−0.0564***	−0.1101***	−0.0537***
$k = 400; d = 17$	0.1056***	0.0504***	0.0219***	−0.0552***	−0.0837***	−0.0285***

‘p > 0.05.

*** p ≤ 0.001.

** p ≤ 0.01.

* p ≤ 0.05.

References

- Ard, K. (2016). By all measures: An examination of the relationship between segregation and health risk from air pollution. *Population and Environment*, 1–20. LaVeist 1993.
- Atkinson, R., & Flint, J. (2004). Fortress UK?: Gated communities, the spatial revolt of the elites and time-space trajectories of segregation. *Housing Studies*, 19(6), 875–892.
- Blumen, O., & Zamir, I. (2001). Two social environments in a working day: Occupation and spatial segregation in metropolitan Tel Aviv. *Environment and Planning A*, 33(10), 1765–1784.
- Brown, L. A., & Chung, S.-Y. (2006). Spatial segregation, segregation indices and the geographical perspective. *Population, Space and Place*, 12(2), 125–143.
- Bullard, R. D. (2000). Anatomy of sprawl. In R. D. Bullard, G. S. Johnson, & A. O. Torres (Eds.). *Sprawl city: Race, politics, and planning in Atlanta* (pp. 1–20). Washington, DC: Island Press.
- Chaix, B., et al. (2013). Neighborhood environments, mobility, and health: Towards a new generation of studies in environmental health research. *Revue d'Épidémiologie et de Santé Publique*, 61, 139–145.
- Cheng, T., & Adepeju, M. (2014). Modifiable temporal unit problem (MTUP) and its effect on space-time cluster detection. *PLoS One*, 9(6), e100465.
- Creese, G. (2011). *The new African diaspora in Vancouver: Migration, exclusion and belonging*. Toronto: University of Toronto Press.
- Dawkins, C. J. (2004). Recent evidence on the continuing causes of black-white residential segregation. *Journal of Urban Affairs*, 26(3), 379–400.
- Dougherty, K. D. (2003). How monochromatic is church membership? Racial-ethnic diversity in religious community. *Sociology of Religion*, 64(1), 65–85.
- Duncan, O. D., & Duncan, B. (1955). A methodological analysis of segregation indexes. *American Sociological Review*, 20(2), 210–217.
- Ellis, M., Wright, R., & Parks, V. (2004). Work together, live apart? Geographies of racial and ethnic segregation at home and at work. *Annals of the Association of American Geographers*, 94(3), 620–637.
- Farber, S., O'Kelly, M., Miller, H. J., & Neutens, T. (2015). Measuring segregation using patterns of daily travel behavior: A social interaction based model of exposure. *Journal of Transport Geography*, 49, 26–38.
- Farber, S., Páez, A., & Morency, C. (2012). Activity spaces and the measurement of clustering and exposure: A case study of linguistic groups in Montreal. *Environment and Planning A*, 44, 315–332.
- Freemark, Y. (2017, Feb 23). *In Atlanta, transit service lags behind a booming population. Streetsblog USA*. Retrieved from <https://usa.streetsblog.org/2017/02/23/in-atlanta-transit-service-lags-behind-a-booming-population/>.
- Grannis, R. (2002). Discussion: Segregation indices and their functional inputs. *Sociological Methodology*, 32(1), 69–84.
- Hägerstrand, T. (1970). What about people in regional science? *Papers of Regional Science Association*, 24, 7–21.
- Hägerstrand, T. (1989). Reflections on “what about people in regional science?”. *Papers of Regional Science Association*, 66, 1–6.
- van Ham, M., & Tammaru, T. (2016). New perspectives on ethnic segregation over time and space. A domains approach. *Urban Geography*, 37(7), 953–962.
- Hatfield, E. A. (2013, April 29). A well-tied knot: Atlanta's mobility crisis and the 2012 T-SPLOST debate. *Southern spaces*. Retrieved from <https://southernspaces.org/2013/well-tied-knot-atlantas-mobility-crisis-and-2012-t-splot-debate>.
- Jang, W., & Yao, X. (2013). Tracking ethnically divided commuting patterns over time: A case study of Atlanta. *The Professional Geographer*, 66(2), 274–283.
- Johnston, R., Poulsen, M., & Forrest, J. (2009). Measuring ethnic residential segregation: Putting some more geography in. *Urban Geography*, 30, 91–109.
- Jones, M., & Pebley, A. R. (2014). Redefining neighborhoods using common destinations: Social characteristics of activity spaces and home census tracts compared. *Demography*, 51(3), 727–752.
- Jones, M. R., Diez-Roux, A. V., Hajat, A., Kershaw, K. N., O'Neill, M. S., Guallar, E., ... Navas-Acien, A. (2014). Race/ethnicity, residential segregation, and exposure to ambient air pollution: The multi-ethnic study of atherosclerosis (MESA). *American Journal of Public Health*, 104(11), 2130–2137.
- Kestens, Y., Lebel, A., Daniels, M., Thériault, M., & Pampalon, R. (2010). Using experienced activity spaces to measure foodscape exposure. *Health and Place*, 16, 1094–1103.
- Krivo, L. J., Washington, H. M., Peterson, R. D., Browning, C. R., Calder, C. A., & Kwan, M.-P. (2013). Social isolation of disadvantage and advantage: The reproduction of inequality in urban space. *Social Forces*, 92(1), 141–164.
- Kwan, M.-P. (2009). From place-based to people-based exposure measures. *Social Science and Medicine*, 69(9), 1311–1313.
- Kwan, M.-P. (2012a). The uncertain geographic context problem. *Annals of the Association of American Geographers*, 102(5), 958–968.
- Kwan, M.-P. (2012b). How GIS can help address the uncertain geographic context problem in social science research. *Annals of GIS*, 18(4), 245–255.
- Kwan, M.-P. (2013). Beyond space (as we knew it): Toward temporally integrated geographies of segregation, health, and accessibility. *Annals of the Association of American Geographers*, 103(5), 1078–1086.
- Kwan, M.-P. (2016). Algorithmic geographies: Big data, algorithmic uncertainty, and the production of geographic knowledge. *Annals of the American Association of Geographers*, 106(2), 274–282.
- Marcińczak, S., Tammaru, T., Strömgren, M., & Lindgren, U. (2015). Changing patterns of residential and workplace segregation in the Stockholm metropolitan area. *Urban*

- Geography*, 36(7), 1–24.
- Morrill, R. L. (1991). On the measure of geographic segregation. *Geography Research Forum*, 11, 25–36.
- National Renewable Energy Laboratory (2016). NREL Transportation secure data center. Retrieved from <http://www.nrel.gov/tsdc>.
- Netto, V. M., Soares, M. P., & Paschoalino, R. (2015). Segregated Networks in the City. *International Journal of Urban and Regional Research*, 39(6), 1084–1102.
- Oka, M., & Wong, D. W. S. (2015). Spatializing segregation measures: An approach to better depict social relationships. *Citiescape*, 17(1), 97–113.
- Openshaw, S. (1984). *The modifiable areal unit problem*. Norwich, England: Geo Books.
- Palmer, J. R. B. (2013). Activity-space segregation: Understanding social divisions in space and time. Ph.D. Dissertation NJ: Princeton University.
- Park, Y. M., & Kwan, M.-P. (2017a). Individual exposure estimates may be erroneous when spatiotemporal variability of air pollution and human mobility are ignored. *Health & Place*, 43, 85–94.
- Park, Y. M., & Kwan, M.-P. (2017b). Multi-contextual segregation and environmental justice research: Toward fine-scale spatiotemporal approaches. *International Journal of Environmental Research and Public Health*, 14(10), 1205.
- Peach, C. (1996). Good segregation, bad segregation. *Planning Perspectives*, 11(4), 379–398.
- Pooley, K. (2015, April 15). Segregation's new geography: The Atlanta metro region, race, and the declining prospects for upward mobility. *Southern spaces*. Retrieved from <https://southernspaces.org/2015/segregations-new-geography-atlanta-metro-region-race-and-declining-prospects-upward-mobility>.
- Reardon, S. F., & O'Sullivan, D. (2004). Measure of spatial segregation. *Sociological Methodology*, 34(1), 121–162.
- Roux, G. L., Vallée, J., & Commenges, H. (2017). Social segregation around the clock in the Paris region (France). *Journal of Transport Geography*, 59, 134–145.
- Sasidharan, V., And, F. W., & Godbey, G. (2005). Cultural differences in urban recreation patterns: An examination of park usage and activity participation across six population subgroups. *Managing Leisure*, 10(1), 19–38.
- Schmitt, A. (2014, Feb 18). MARTA expansion could help reverse Atlanta's legacy of racial segregation. *Streetsblog USA*. Retrieved from <https://usa.streetsblog.org/2014/02/18/expansion-could-begin-to-reverse-martas-legacy-of-racial-segregation/>.
- Schnell, I., & Yoav, B. (2001). The sociospatial isolation of agents in everyday life spaces as an aspect of segregation. *Annals of the Association of American Geographers*, 91(4), 622–636.
- Schönfelder, S., & Axhausen, K. W. (2003). Activity spaces: Measures of social exclusion? *Transport Policy*, 10(4), 273–286.
- Shareck, M., Kestens, Y., & Frohlich, K. L. (2014). Moving beyond the residential neighborhood to explore social inequalities in exposure to area-level disadvantage: Results from the interdisciplinary study on inequalities in smoking. *Social Science and Medicine*, 108, 106–114.
- Shelton, T., Poorthuis, A., & Zook, M. (2015). Social media and the city: Rethinking urban socio-spatial inequality using user-generated geographic information. *Landscape and Urban Planning*, 142, 198–211.
- Silm, S., & Ahas, R. (2014). The temporal variation of ethnic segregation in a city: Evidence from a mobile phone use dataset. *Social Science Research*, 47, 30–43.
- Silver, N. (2015, May 1). The most diverse cities are often the most segregated. *Five thirty eight*. Retrieved from <http://fivethirtyeight.com/features/the-most-diverse-cities-are-often-the-most-segregated/>.
- Strait, J. B., & Gong, G. (2015). The impact of increased diversity on the residential landscape of a sunbelt metropolis: Racial and ethnic segregation across the Atlanta metropolitan region, 1990–2010. *Southeastern Geographer*, 55(2), 119–142.
- Tobler, W. (1970). A computer movie simulating urban growth in the Detroit region. *Economic Geography*, 46(2), 234–240.
- Toomet, O., Silm, S., Saluveer, E., Ahas, R., & Tammaru, T. (2015). Where do ethno-linguistic groups meet? How copresence during free-time is related to copresence at home and at work. *PLoS One*, 10(5), e0126093.
- Vallas, S. P. (2003). Rediscovering the color line within work organizations: The 'knitting of racial groups' revisited. *Work and Occupations*, 30(4), 379–400.
- Wang, D., & Li, F. (2015). Daily activity space and exposure: A comparative study of Hong Kong's public and private housing residents' segregation in daily life. *Cities*. <http://dx.doi.org/10.1016/j.cities.2015.09.010>.
- Wang, D., Li, F., & Chai, Y. (2012). Activity spaces and sociospatial segregation in Beijing. *Urban Geography*, 33(2), 256–277.
- White, M. J. (1983). The measurement of spatial segregation. *American Journal of Sociology*, 88, 1008–1018.
- White, M. J. (1986). Segregation and diversity: Measures in population distribution. *Population Index*, 52, 198–221.
- Wong, D. W. S. (1993). Spatial indices of segregation. *Urban Studies*, 30, 559–572.
- Wong, D. W. S. (2004). Comparing traditional and spatial segregation measures: A spatial scale perspective. *Urban Geography*, 25(1), 66–82.
- Wong, D. W. S. (2016). From aspatial to spatial, from global to local and individual: Are we on the right track to spatialize segregation measures? In F. M. Howell, J. R. Porter, & S. A. Matthews (Eds.), *Recapturing space: New middle-range theory in spatial demography* (pp. 77–98). Switzerland: Springer International Publishing.
- Wong, D. W. S., & Shaw, S.-L. (2011). Measuring segregation: An activity space approach. *Journal of Geographical Systems*, 13, 127–145.
- Wright, R., Ellis, M., & Parks, V. (2010). Immigrant niches and the intrametropolitan spatial division of labour. *Journal of Ethnic and Migration Studies*, 36(7), 1033–1059.
- Zenk, S. N., Schulz, A. J., Matthews, S. A., Odoms-Young, A., Wilbur, J., Wegryn, L., ... Stokes, C. (2011). Activity space environment and dietary and physical activity behaviors: A pilot study. *Health and Place*, 17(5), 1150–1161.
- Zhang, W., & Thill, J.-C. (2017). Detecting and visualizing cohesive activity-travel patterns: A network analysis approach. *Computers, Environment and Urban Systems*, 66, 117–129.